Dear Reviewer,

We sincerely thank you for the positive and constructive feedback. We greatly appreciate your recognition of the relevance of our study, as well as your acknowledgement of the clarity and significance of our objectives and the contribution this work makes to the current state of the art in fatigue assessment of offshore wind turbine substructures.

Your comments were highly insightful and have helped us enhance the clarity, completeness, and scientific quality of the manuscript. We have carefully addressed each comment and have revised the manuscript accordingly, providing additional explanations, clarifications, and references where necessary.

We genuinely appreciate the time and effort you have devoted to reviewing our work.

In our response:

- The reviewer comments are in Black and
- Author replies are in Red, and
- The changes made to the manuscript are marked in Blue

The topic of the paper is very relevant, and the approach followed—anchored in two large datasets of experimental data collected from two operating wind turbines and exploring many alternative models—is quite valuable.

The objectives of the paper are clearly stated and pertinent. As the authors state at the end of the paper, some of the conclusions might depend on the site and turbine model, but still, the in-depth analysis and the results obtained for two significantly different offshore models represent an important contribution to the current state of the art.

The following points could be improved:

- **Section 3.1** – In the strain data processing, it is relevant to mention that before converting strains to stresses, it is crucial to remove the effects of temperature (this is not mentioned in the paper, but there is probably a temperature sensor next to each strain gauge) and any potential strain drift over time (these are more critical in electrical strain gauges; the paper does not specify whether the strain gauges are electrical or fiber-optic sensors).

  We thank the reviewer for this comment. The monitoring system uses electrical strain gauges, each equipped with an adjacent thermocouple for temperature compensation. Potential drift in strain measurements over time is mitigated through periodic recalibration of the strain gauges data.
  In response, we have added the following clarification to the manuscript:

“The data from six circumferential electrical strain gauges is pre-processed using the steps shown in Fig. 3. Each strain gauge is installed together with a dedicated thermocouple to enable temperature compensation. This temperature compensation as well as any long-term measurement drift is addressed through continuous follow-up and periodic recalibration of the strain gauges data by the SHM hardware supplier.”

- **Figure 3** – In the strain pre-processing, it would be preferable to convert measured stresses to bending moments (this needs to be explained, since with the use of six measuring points, a fitting procedure should be devised). These could then be oriented in the compass direction or in the FA/SS direction, and from these, the stresses at any point of the cross-section could be obtained. The naming “stresses in FA and SS direction” is misleading—the stresses under analysis are vertical!

We thank the reviewer for this comment. We agree that the conversion from measured strains to bending moments requires explanation. We also acknowledge that the naming “stresses in FA and SS direction” may be misleading, since the stresses of interest are axial stresses resulting from FA and SS bending moments rather than stresses acting in horizontal directions.
To address this, we have added the following detailed clarification in the manuscript:
“From the measured strains at the six circumferential sensors, the corresponding stresses and bending moments are obtained through a two-step procedure. First, the axial stress at each sensor location is computed using Hooke’s law (Equation (1)):

$$\sigma_{zz,j} = E\ \varepsilon_{zz,j}$$

where E is Young’s modulus, and $\varepsilon_{zz,j}$ and $\sigma_{zz,j}$ are the measured axial strain and resulting axial stress at the j-th sensor, respectively.
The general equation for normal stress $\sigma_{zz,j}$ induced by a normal force F_N and the global bending moments M_{NS} (North-South) and M_{EW} (East-West) in cylindrical coordinates is given in Equation (2):

$$\sigma_{zz,j} = \left(\frac{F_N}{A}\right) + R_i \cdot \left[\frac{M_{NS}}{I_C} . sin\left(\theta_j\right) - \frac{M_{EW}}{I_C} \cdot cos\left(\theta_j\right)\right],$$

where A is the cross-sectional area, R_i is the inner radius at the sensor location, I_C is the area moment of inertia, and θ_j is the clockwise angular position of the j-th sensor from the North-South axis. Equation (2) can be written for each sensor.
With six sensors, this formulation yields an overdetermined system that is solved using a least-squares fitting procedure to estimate the normal load F_N and bending moments in both directions M_{NS} (North-South) and M_{EW} (East-West)

from the measurements (see Sadeghi et al. (2023a) and Link and Weiland (2014) for more details for more details).

The resulting bending moments are then rotated in fore-aft (FA) and side-side (SS) direction using Equation (3):

$$\begin{Bmatrix} M_{FA} \\ M_{SS} \end{Bmatrix} = \begin{bmatrix} \cos(-\psi + \pi) & \sin(-\psi + \pi) \\ -\sin(-\psi + \pi) & \cos(-\psi + \pi) \end{bmatrix} \begin{Bmatrix} M_{NS} \\ M_{EW} \end{Bmatrix}$$

Where ψ is the mean yaw angle within each 10-minute interval. This transformation yields the fore-aft (M_{FA}) and side-side (M_{SS}) bending moments , also defined as normal bending moment (M_{tn}) and lateral bending moment (M_{tl}) respectively in IEC61400-13 (2021).

Stresses in fore-aft direction refer to axial stresses caused by fore-aft bending moment (M_{FA}) and stresses in side-side direction refer to axial stresses caused by side-side bending moment (M_{SS}).”

- **Equation (1)** – In design codes, the fatigue of steel elements is calculated using a bi-linear S-N curve with m equal to 3 and 5. This should be commented on.

  We thank the reviewer for this comment. We have clarified in the manuscript that design standards prescribe a bilinear S-N curve with slopes 3 and 5 for welded steel details. We have added the following description in the paper:

  “The slope (m) and intercept ($\log(\bar{a})$) defining the S-N curve depend on the fatigue detail, environmental conditions, and material properties, and are provided in DNV-RP-C203 (2024) guidelines. In this study, the bilinear DNV D-A curve for a D-detail (circumferential butt weld made from both sides) is adopted, with slopes of m = [3, 5] and intercepts of $\log(\bar{a})$ = [12.164, 15.606], with a transition at 10^7 cycles.”

- **Section 3.2** – The following sentence is unclear: “Invalid operational states refer to intervals lacking valid SCADA-derived statistics, typically involving transient events such as rotor start-up or shutdown.” Transient events are not considered in fatigue accumulation? Please clarify this point.

  We thank the reviewer for this comment. In our workflow, each 10-minute data block is assigned to an operational state based on SCADA-derived statistics. Blocks that occur during transient events (e.g. start-up, shutdown) do not satisfy the thresholds used to classify predefined operational states and therefore receive the label *“Invalid” referring to “transient” operational state*. This label refers only to the *operational state classification* and does not imply that the data are excluded from fatigue analysis. All data intervals, including those in intervals labelled *“Invalid”*, are included in the fatigue damage accumulation.

The manuscript has been updated to replace “invalid” with “transient” to avoid confusion.

“Intervals that occur during turbine transients (e.g. start-up, shutdown) fall outside the predefined statistical thresholds on SCADA statistics and are therefore labelled *transient*.”

- **Section 5, Table 3** – Some candidates for selected variables present strong correlations. Please clarify how this correlation may have influenced the selection of the features.

  We thank the reviewer for this comment. While some of the selected features exhibit correlations, the Random Forest feature importance metric inherently accounts for the contribution of each variable in reducing node impurity across all trees. Therefore, even correlated features can provide incremental predictive power, and the ranking reflects their combined impact on model performance. We have added the following clarification in the revised manuscript.

  “Some of the selected features exhibit correlations. Random Forest feature importance evaluates each variable’s contribution to reducing node impurity across all trees, so correlated variables can still be selected if they provide incremental predictive information (Breiman (2001)). The top five features are thus those with the highest combined predictive relevance, and their selection reflects the overall importance rather than strict independence. Future work could explore dimensionality reduction methods to explicitly account for feature correlation.”

- **Section 5.1** – The most standard variables used for fatigue estimation with SCADA data are wind velocity and turbulence. It would be useful to compare a model just based on these variables with all the others that have been tested.

  We thank the reviewer for this comment. While wind speed and turbulence intensity are indeed standard variables for fatigue estimation, our study focuses on identifying the most relevant features based on the Random Forest feature importance metric. Turbulence intensity is selected for nearly all target variables (except the side-side direction of the 9 MW OWT), and the binning approaches includes wind speed and turbulence intensity alongside other top-ranked features. We acknowledge the value of a comparison with a model using only standard variables; however, this is beyond the scope of the current study, which emphasizes incremental feature selection and its impact on predictive performance. We have added reference to earlier relevant work along with the following lines in the paper to address the reviewers comment:

“While wind speed and turbulence intensity are commonly used for fatigue estimation (as studied by Noppe et al. (2020) on 2MW OWT), our feature selection approach identifies variables that provide the greatest incremental predictive value for each target. Turbulence intensity is selected for most targets, and wind speed is included in all binning strategies (except for side-side direction of 9MW OWT), ensuring that standard fatigue predictors are considered alongside additional influential features.”